INVESTMENT COSTS OPTIMIZATION OF MULTI-ROBOT SYSTEM USING GENETIC ALGORITHM

Vitālijs Komašilovs
Latvia University of Agriculture
e-mail: vitalijs.komasilovs@gmail.com

Abstract
Forethought deployment of an industrial production system is a significant step towards improving economic benefit of an industrial company. The author proposes the procedure for finding an optimal specification of multirobot system, which considers it on the level of components of the robotic system. Components are grouped into mobile or stationary units of the system. A set of agents is considered as a solution for particular mission, it defines a specification of a heterogeneous multi-robot system. The paper presents the concept of the optimization procedure and describes the implementation of investment costs optimization step, which uses genetic algorithm.
Key words: multi-robot system, optimization, genetic algorithm.

Introduction

Last decade is peculiar by a growth of applications of robotic system in various fields. Robotic systems are being for such purposes as production process automation (Jammes and Smit, 2005) and intelligent manufacturing (Almeida, 2011). An increasing number of applications is reported in such domains as medicine (Davies, 2010), elderly care (Hansen et al., 2010) or daily life as household companions (Parlitz et al., 2007). An increasing interest in the research of heterogeneous multi-robot systems is caused by variety of their advances in comparison with homogeneous robotic systems (Shen and Norrie, 1999; Bi et al., 2008). Because of expected increase of the demand for heterogeneous robotic systems, the task of design and development of an optimal system becomes important (Kiener and Stryk, 2010). The economic benefit of a company depends on the effectiveness of robotic production system.

Active researches within robotics field primarily focus on novel methods for such aspects as intelligent control (Nouyan et al., 2009), world modeling (Coltin et al., 2010), communication (Mathews et al., 2011), etc., but the configuration of the system is not considered among the improvable parameters and is usually predefined or selected intuitively. However, the performance of the whole system is strongly influenced by characteristics and functionalities of the individual robots (Levi and Kernbach, 2010). The author proposes a specification optimization procedure, which purpose is to overcome aforementioned drawbacks.

The paper describes a concept of proposed optimization procedure and presents investment costs estimation model for heterogeneous robotic system which is used for evaluation of solution candidates. The implementation of evaluation step of specification optimization procedure is described in details. It is based on genetic algorithm (Holland, 1975) and uses costs estimation model as an objective function.

Materials and Methods

The specification of a multi-robot system defines types of agents (classes), their functions as well as a number of instances of each class of agents in the system. Optimal specification of a multi-robot system is such a configuration of the system that maximizes the objective function. The author uses investment costs as a primary evaluation criterion for current research. Investment costs define all expenses required to design, implement and deploy a multi-robot system from the scratch into production environment and do not include expenses related to the operation of the system. A usual business requirement is to reduce investment costs, therefore an inversed optimization objective function is used.

According to the developed specification optimization procedure, several concepts have been defined (see Figure 1). *Component* stands for a definition of function of the robotic system. Components are grouped together in order to form an *agent* (rather, mobile robot or a stationary unit). *Solution* is a specification of a heterogeneous robotic system, it defines types of agents and a number of their instances used to carry out a mission. A number of rules is applied before considering any combination of agents as a solution.

Figure 1. Conceptual model of the solution.

Figure 2. Specification optimization procedure.

Specification optimization procedure specifies three consecutive steps (see Figure 2). First of all, business requirements are defined by an industrialist, and then the optimization objective function is developed. Finally, heuristic algorithms are used to find the fittest solution. Detailed description of steps of the procedure is provided in (Komasilovs and Stalidzans, 2012).

An investment costs estimation model is developed with the aim to perform fast evaluation of a large number of solution candidates. According to the concept of specification optimization procedure, the mission for a multi-robot system is defined using a list of components. Investment costs model assumes that components have additional properties, which are related to the costs of a particular component.

Investment costs could be divided into several positions described below. The proposed model imply that investment costs of the whole system (Q_{inv}) equal to the sum of investment expenses for agents (Q_{inv_agent}). Expenses for system design are applied as an additional fraction (c_{sys_design} coefficient):

$$Q_{inv} = (1 + c_{sys\_design}) \times \sum Q_{inv\_agent} \quad (1)$$

Investment costs of agent (Q_{inv_agent}) consist of design costs of a particular type of agents (Q_{design}) and production expenses (Q_{prod}) of all instances of a particular class of agents:

$$Q_{inv\_agent} = Q_{design} + Q_{prod} \times N_{inst} \quad (2)$$

Design costs (Q_{design}) depend on the number of components (N_{comp}) involved into design of a particular class of agents, and the author assume that it grows exponentially. Coefficients (c_{lin} and c_{exp}) are used to tune the growth dynamics according to real prices of the design:

$$Q_{design} = c_{lin} \times exp\ (c_{exp} \times N_{comp}) \quad (3)$$

Production costs of an agent (Q_{prod}) equal to the sum of expenses, required to purchase the components (Q_{comp}) as well as agent assembly expenses (Q_{assy}):

$$Q_{prod} = \sum Q_{comp} + Q_{assy} \quad (4)$$

Assembly costs of an agent (Q_{assy}) grow exponentially depending on the number of components used in the agent (N_{comp}):

$$Q_{assy} = c_{lin} \times exp\ (c_{exp} \times N_{comp}) \quad (5)$$

Values of Q_{comp} for each component are defined by the user of optimization procedure; coefficients c_{lin} and c_{exp} both for design and assembly costs are defined on the level of an optimization problem.

Results and Discussion

The paper describes implementation of the third step of a multi-robot system specification optimization procedure which uses investment costs estimation model presented in the previous chapter. The author uses genetic algorithm as a heuristic optimization method. In general, genetic algorithm mimics the processes of natural evolution such as inheritance, mutation, selection and crossover. The population of solution candidates evolves towards better solutions through generations. The fitness of every solution candidate is evaluated in each iteration, and the fittest candidates are used to form the next generation (Eiben and Smith, 2003).

One of the most challenging aspects in any application of a genetic algorithm is the development of a fitness function which is used to evaluate solution candidates in each iteration. The author uses costs estimation model as a fitness function for the genetic algorithm described in the previous section.

Another challenging aspect is the implementation of genetic representation of a solution domain. It should cover complete solution space and be stable against local extremes. According to the concept, a solution is a set of agents. Thus, every solution candidate should encode such set of agents. There are two attributes related to a particular agent: class of agent, and the number of its instances used in the solution. Because of the requirement to cover a full space of solutions, all types of agents should be encoded within a chromosome.

Classic application of a genetic algorithm implies the use of bit-value genes. In case of specification optimization problem, such genes could define types of agents, but not the number of instances. Also it is possible to add additional bit genes for encoding the number of instances, but in such case the number of

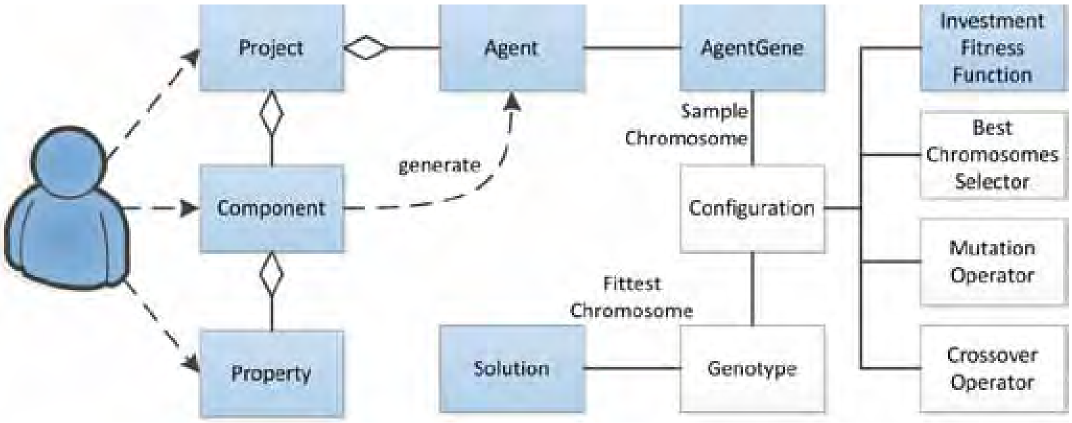

Figure 3. Conceptual object diagram.

genes within a chromosome (its length) would grow dramatically.

Because of that the author has selected integer genes to encode the set of selected agents within the chromosome. The range of values of agent genes is limited to non-negative integers. Gene with a value of zero means that particular type of agents is not used in the solution. Genetic operators for such genes are implemented randomly changing the value of the gene by the defined threshold.

The multi-robot system specification optimization software was developed using Java programming language and JGAP genetic algorithms package (Meffert et al., 2012). A number of special objects were involved into implementation of specification optimization procedure (see Figure 3): objects from JGAP package (white), as well as custom objects (gray).

Every specification optimization case (the mission) is defined as a project. The user defines a list of components required for performing the mission, as well as properties of these components. Then the list of components is used to automatically generate the list of possible agent classes. The optimization problem for a genetic algorithm is defined trough a special configuration object. It has a lot of specific properties; most important of them is the sample chromosome, which is used to breed the population of solution candidates. Agent genes are used in the sample chromosome. They are the extension of integer genes with the only added field, which refers to the agent instance they represent.

Another important object related to configuration of the genetic processor is the custom fitness function, which in this case implements the investment costs estimation model described above. Configuration also allows specifying a number of genetic operators involved into processing. Natural selection is implemented by selecting best 90% of solution candidates into breeding of the next generation. Mutation operator is applied to genes with probability of 0.08. Crossover is applied to 35% of candidates selected for the next generation.

Configuration object specifies also general properties for the genetic algorithm, such as maximum size of population (value of 200 was used in implementation) or allowance of identical individuals. After setting all required properties, the configuration object is used to create a genotype – the population of solution candidates. Then genotype evolves according to the specified fitness function and genetic operators. The number of generations is limited to 500. After finishing evolution, a solution of the optimization problem (the best specification of the multi-robot system in terms of investment costs) can be retrieved from the fittest chromosome of the genotype.

Conclusions

1. The paper presents investment costs estimation model for a heterogeneous multi-robot system. Investment costs for a particular system are estimated using user specified properties of the components (e.g. price). Also an assumption is used within the model, according to which the design and assembly costs of an agent (a robot, in particular) grow exponentially from the number of components used in it.
2. The implementation of heuristic evaluation is based on a genetic algorithm. The optimization task setup is described in the paper, as well as the software implementation model is presented. Adjusted parameters of the genetic algorithm allowed a fast and reliable evaluation of the solution candidates. The fitness function of the genetic algorithm corresponds to investment costs estimation model.
3. Specification optimization procedure was developed as a formal analysis method for heterogeneous multi-robot systems and it allows elimination of non-optimal solution branches with minimal effort.

Acknowledgements

Academic study and publication is financed by the project "Support for doctoral studies in LLU" /2009/0180/1DP/1.1.2.1.2/09/IPIA/VIAA/017/ agreement No. 04.4-08/EF2.D1.05.

References

1. Almeida F.L.F. (2011) Designing and implementation of an intelligent manufacturing system. *Journal of Industrial Engineering and Management*, 4(4), pp. 718–745.
2. Bi Z.M., Lang S.Y.T., Shen W., Wang L. (2008) Reconfigurable manufacturing systems: the state of the art. *International Journal of Production Research*, 46(4), pp. 967–992.
3. Coltin B., Liemhetcharat S., Meriçli Ç., Veloso M. (2010) Challenges of Multi-Robot World Modelling in Dynamic and Adversarial Domains. In *Workshop on Practical Cognitive Agents and Robots, 9th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2010)*. Available at: http://cetin.mericli.com/files/coltinAAMAS2010WorldModeling.pdf, 19 January 2012
4. Davies B. (2010) A review of the state-of-the-art of "smart" systems in surgery. *International Journal of Intelligent Systems*, 8(1/2/3/4), p. 423.
5. Eiben A.E., Smith J.E. (2003) *Introduction to evolutionary computing*, Berlin, Germany: Springer Verlag, p. 415.
6. Hansen S.T., Andersen H.J., Bak T. (2010) Practical evaluation of robots for elderly in Denmark: An overview. In *Proceeding of the 5th ACM/IEEE international conference on Human-robot interaction*. ACM, pp. 149–150.
7. Holland J.H. (1975) *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*, Ann Arbor, Michigan: University of Michigan Press. Available at: http://www.openisbn.com/isbn/0262581116/, 19 January 2012
8. Jammes F., Smit H. (2005) Service-Oriented Paradigms in Industrial Automation. *IEEE Transactions on Industrial Informatics*, 1(1), pp. 62–70.
9. Kiener J., Stryk O. (2010) Towards cooperation of heterogeneous, autonomous robots: A case study of humanoid and wheeled robots. *Robotics and Autonomous Systems*, 58(7), pp. 921–929.
10. Komasilovs V., Stalidzans E. (2012) Procedure of Specification Optimization of Heterogeneous Robotic System. In *IEEE 10th Jubilee International Symposium on Applied Machine Intelligence and Informatics (SAMI)*. Herl'any, Slovakia: IEEE, pp. 259–263.
11. Levi P., Kernbach S. (2010) Heterogeneous Multi-Robot Systems. In R. Dillmann, D. Vernon, Y. Nakamura, and S. Schaal, eds. *Symbiotic Multi-Robot Organisms*. Springer Berlin Heidelberg, pp. 79–163.
12. Mathews N., Christensen A., Dorigo M. (2011) Cooperation in a heterogeneous robot swarm through spatially targeted communication. *Swarm Intelligence*, pp. 400–407.
13. Meffert K., Meseguer J., Martн E.D., Meskauskas A., Vos J., Rotstan N. (2012) JGAP - Java Genetic Algorithms and Genetic Programming Package. Available at: http://jgap.sf.net, 19 January 2012.
14. Nouyan S., Grob R., Bonani M., Mondada F., Dorigo M. (2009) Teamwork in Self-Organized Robot Colonies. *IEEE Transactions on Evolutionary Computation*, 13(4), pp. 695–711.
15. Parlitz C., Baum W., Reiser U. (2007) Intuitive human-machine-interaction and implementation on a household robot companion. *Human Interface and the Management of Information. Methods, Techniques and Tools in Information Design*, (01), pp. 922–929.
16. Shen W., Norrie D.H. (1999) Agent-Based Systems for Intelligent Manufacturing: A State-of-the-Art Survey. Available at: http://www.eurescom.eu/~public-webspace/p800-series/P815/web/Papers/Agents/abm.htm#sec410, 19 January 2012.